NICE 2022

Temporal and Spatio-temporal domains for Neuromorphic Tactile Texture Classification

George Brayshaw, Martin J. Pearson, Benjamin Ward-Cherrier

Bristol Robotics Laboratory

UWE Bristol University of the West of England

University of BRISTOL

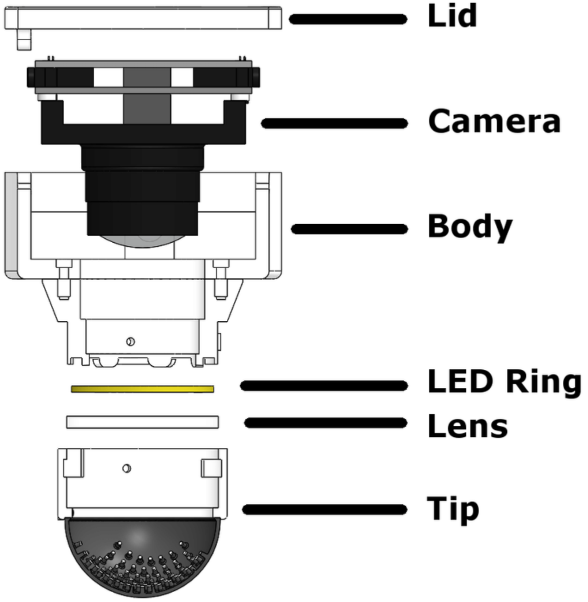
UKRI Engineering and Physical Sciences Research Council

Motivations

- Systems to sense and process textures in a biologically plausible manner
  - Manipulators
  - Prosthesis
- Neuromorphic sensors/cameras and spiking neural networks

Research Goal

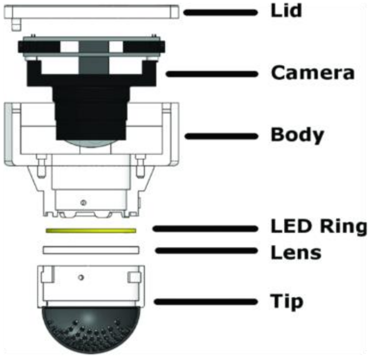
Evaluate the viability of simple classifiers for use with a neuromorphic texture dataset

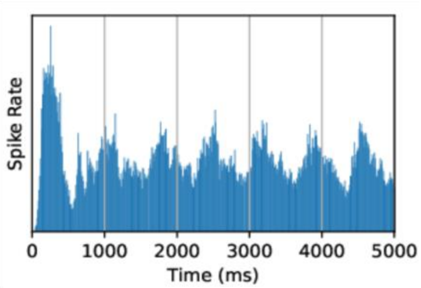


[1]B. Ward-Cherrier, N. Pestell, and N. F. Lepora, "***Neurotac: A neuromorphic optical tactile sensor applied to texture recognition***"

Methodology

- Dataset of natural and 3D printed textures
  - 22 textures x 100 trials
- Application of simple classifiers to temporal and spatio-temporal data
  - KNN, Naïve Bayes & MLP
  - Hierarchy Of event-based Time Surfaces (HOTS)[2]

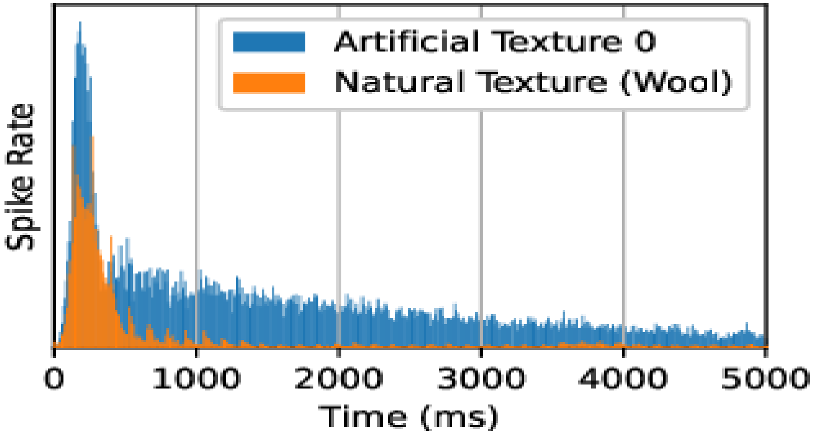




[2]X. Lagorce, et al. "**Hots: a hierarchy of event-based time-surfaces for pattern recognition**," IEEE transactions on pattern analysis and machine intelligence, vol. 39, no. 7, pp. 1346–1359, 2016

Temporal Data

$$Rep(T) = \sum_{n=1}^{N} \sum_{t=T}^{T+\Delta T} t_n^i$$

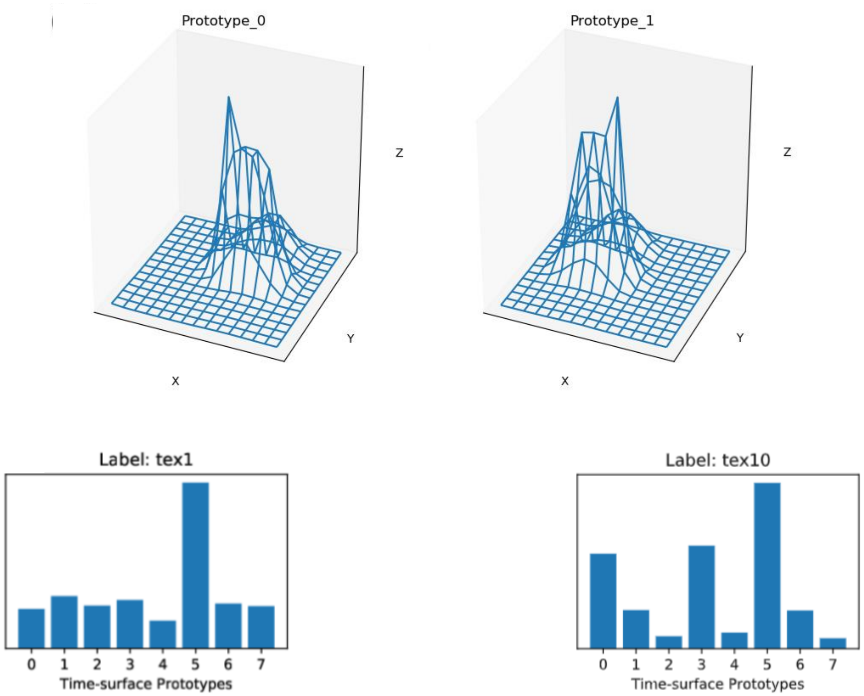


Rep(T) gives an encoded representation of the incoming spike train, within a moving time window of size ΔT moving in 1ms increments where t_n^i *is a spike time event with index i for pixel n and N is the total number of pixels.*

Hierarchy Of event-based Time Surfaces (HOTS)

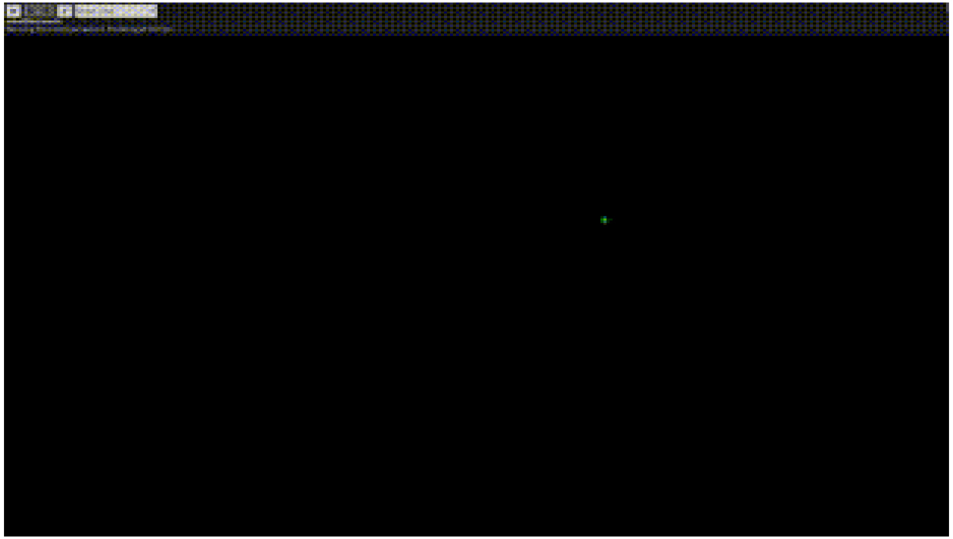
- Spatio-temporal classifier that builds time surfaces based on local pixel activity

- Histograms are created for each label with Euclidean distance between histograms used for classification



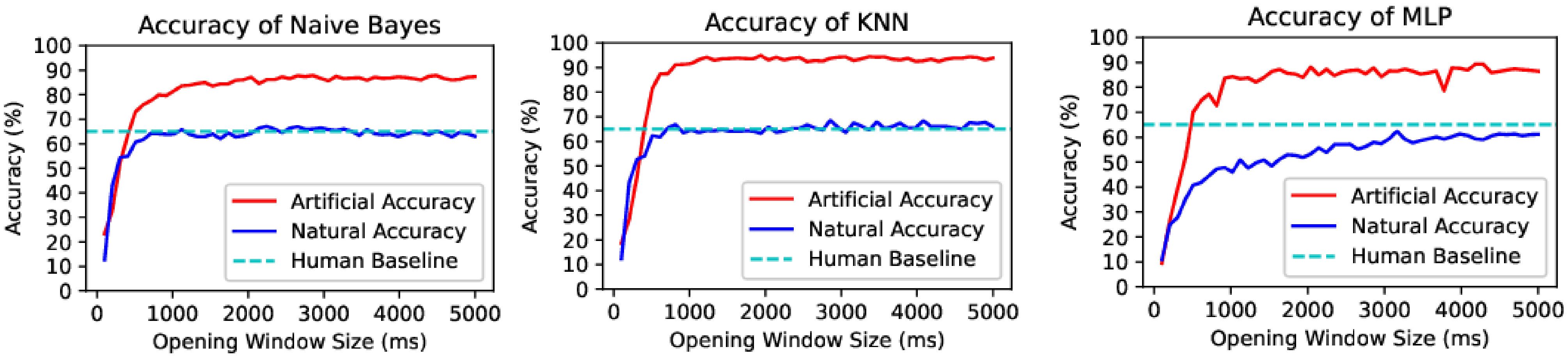
[2]X. Lagorce, et al. “**Hots: a hierarchy of event-based time-surfaces for pattern recognition**,” IEEE transactions on pattern analysis and machine intelligence, vol. 39, no. 7, pp. 1346–1359, 2016

Time for Classification (t_C)



t_c metric indicates how much data is required for *accurate* classification. It is the length of training data provided to achieve 90% of final accuracy

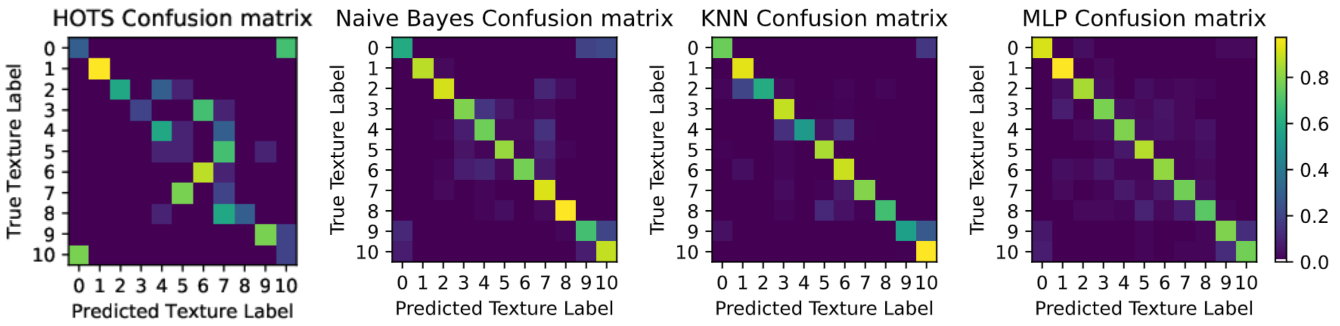
Time for Classification (t_C) cont.



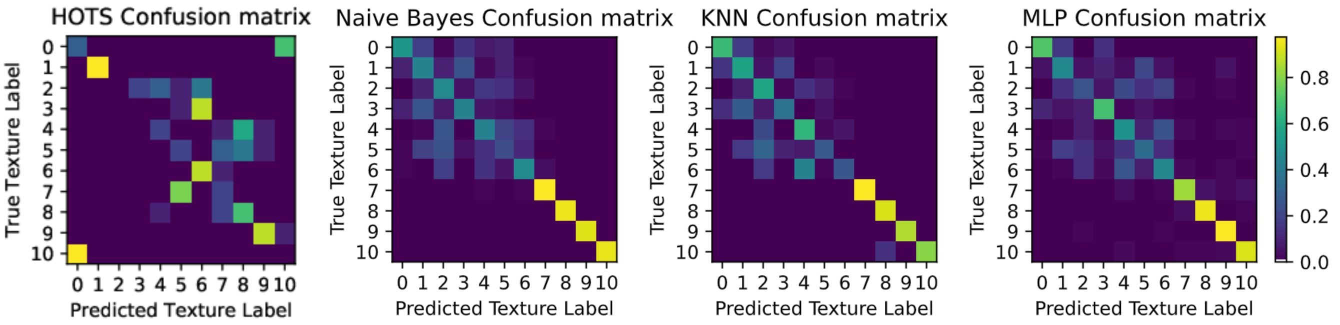
Results

Dataset	Metric	Algorithm			
		Naïve Bayes	**KNN**	**MLP**	**HOTS**
Artificial	**Peak Accuracy (%)**	*85*	*91*	*84*	*50*
	t_c (ms)	*400*	*500*	*700*	-
Natural	**Peak Accuracy (%)**	*70*	*69*	*64*	*40*
	t_c (ms)	*500*	*500*	*2300*	-

Results Cont.



(a) Artificial Textures



(b) Natural Textures

Texture Label	Texture Material
0	Acrylic
1	MDF
2	Foam
3	Plywood
4	Microdot Foil
5	Metallic Mesh
6	Liquid Satin
7	Felt
8	Fleece
9	Fake Fur
10	Wool

Conclusions & Future Work

Conclusions

- Temporal element of data more important within our application
- HOTS fails to be scalable for this application
- Lower accuracies given for natural textures

Future Work

- Results are informing the design of spiking networks
- Additional functionality planned to aid with confusing textures
- Miniaturisation of neuroTac under development

References

[1]B. Ward-Cherrier, N. Pestell, and N. F. Lepora, “**Neurotac: A neuromorphic optical tactile sensor applied to texture recognition**,” in 2020 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2020, pp. 2654–2660.

[2]X. Lagorce, et al. “**Hots: a hierarchy of event-based time-surfaces for pattern recognition**,” IEEE transactions on pattern analysis and machine intelligence, vol. 39, no. 7, pp. 1346–1359, 2016